Future Ensemble-Based Hurricane Forecast Products

Thomas M. Hamill[1], Michael J. Brennan[4], Barbara Brown[2], Mark DeMaria[3], Edward N. Rappaport[4], and Zoltan Toth[5]

[1] *NOAA Earth System Research Lab, Physical Sciences Division, Boulder, Colorado*
[2] *NCAR, Research Applications Lab, Boulder, Colorado*
[3] *NOAA NESDIS, Ft. Collins, Colorado*
[4] *National Hurricane Center, Miami, Florida*
[5] *NOAA Earth System Research Lab, Global Systems Division, Boulder, Colorado*

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Corresponding author address

Dr. Thomas M. Hamill
NOAA Earth System Research Lab
R/PSD 1
325 Broadway
Boulder, CO 80305-3328
tom.hamill@noaa.gov
(303) 497-3060 phone
(303) 497-6449 fax

ABSTRACT

Tropical cyclone (TC) forecast products may be enhanced by including uncertainty information from ensembles. A workshop was held at the National Center for Atmospheric Research (NCAR) in Boulder, Colorado in April 2010 to: (1) review progress in ensemble prediction of TCs and the scientific issues in ensemble system development for TCs; (2) discuss the needs of forecasters and other users for uncertainty information, including what new ensemble-based products may be the most useful in the near future; and (3) assign priorities to the development of specific ensemble-based products. A discussion of progress on ensemble prediction related to TCs and the recommendations and relative priorities from this workshop are presented. These recommendations are the starting point for a community-wide discussion of how to leverage ensemble-based uncertainty information for TC prediction.

CAPSULE:

Ensemble prediction for tropical cyclones is rapidly maturing. Some potential new uncertainty products are proposed, synthesizing recommendations from a 2010 workshop.

1. Introduction

Uncertainty is inevitable in any weather forecast, a consequence of chaotic growth of initial condition errors (Lorenz 1996) and model imperfections. Quantifying this uncertainty may be particularly beneficial for tropical cyclone forecasts. For example, rather than assuming some standard 225-km position error[1] for a 3-day forecast, a reliable uncertainty estimate of 150 km in one circumstance and 300 km in another should facilitate informed case-by-case decisions on the extent of coastline evacuation (Fig. 1). Studies have shown that users prefer receiving uncertainty information rather than having that information hidden from them (Morss et al. 2008). When no uncertainty information is provided, users tend to estimate the uncertainty on their own anyway (Joslyn and Savelli 2010). Better decisions are made when reliable uncertainty information is provided (Joslyn et al. 2007, Nadav-Greenberg and Joslyn 2009), and users are more likely to use marginal forecasts and become more fault-tolerant of forecast misses when the expected error is quantified (LeClerc and Joslyn 2009).

To provide weather-dependent uncertainty estimates, ensemble prediction techniques have been widely adopted. Multiple, parallel forecast simulations are typically generated from slightly different initial conditions. Increasingly, the different member forecasts may also incorporate stochastic dynamics, different parameterizations, or may even use different models in order to also estimate the uncertainty contributed by model imperfections.

[1] An estimate chosen arbitrarily for purpose of illustration.

Probabilistic information has been provided with hurricane forecasts for several decades. For example, in 1983 the National Weather Service (NWS) implemented quantitative products that provided “strike” probabilities of tropical cyclones (TCs) tracks coming within 60 nautical miles (111 km) of specified coastal locations (Sheets 1985). Beginning in 2006, these were replaced with more general surface wind probability products that include information about the uncertainty in the track, intensity and wind structure forecasts (DeMaria et al. 2009). The original track probabilities and the more recent wind probability products are primarily statistically based, where the uncertainty information is determined from error statistics of operational track, intensity and structure forecasts from previous years. In 2010, a small step toward incorporating real-time ensemble model-based information was initiated. In particular, the track error distributions that are utilized to generate the probabilities are being stratified based on the spread of the tracks from several deterministic forecast models (Kidder et al. 2009).

An advantage of the current statistically based NWS TC probability products is that they provide an accurate measure of the average uncertainty in the operational tropical cyclone forecasts. A disadvantage is that they provide very little information about an individual forecast situation, especially with regard to intensity and structure uncertainty. Conceptually, providing situation-dependent uncertainty forecasts based on ensembles appears to be straightforward. However, uncertainty estimates that are formulated directly from current-generation model-based ensembles tend to be overly confident, offering unrealistically narrow range of solutions and often biased uncertainty estimates. This may be a consequence of one of many ensemble system deficiencies; the method of initializing the ensemble may not fully represent the analysis uncertainty and the important growing error structures, the ensembles may be based on models that have significant imperfections, and the ensemble system may treat some forecast processes as deterministic rather than stochastic. These may be addressed through ensemble system improvements and/or post-processing using past forecast cases and observations.

As these ensemble systems are improved and are able to provide increasingly reliable TC uncertainty guidance, the TC product developers should be ready to provide visually effective ensemble-based forecast products to forecasters, emergency managers, broadcasters, the media, and other users. Deciding what initial products may be of the most value was the primary objective of a 2010 workshop in Boulder, Colorado. About 50 ensemble prediction experts, meteorologists with expertise in statistics, hurricane forecasters, and representatives from the emergency management and social-science communities attended the workshop, in person or over the phone. They discussed what enhancements were desirable and likely to be possible with upcoming ensemble prediction systems, and recommended several new ensemble-based products. The workshop was held at the National Center for Atmospheric Research (NCAR) on 20-21 April 2010.

The rest of this article will briefly review some of the scientific challenges related to ensemble prediction of TCs (section 2). It will then describe consensus recommendations regarding what products should be developed in the next several years (section 3), and offer conclusions about the results of the workshop and the way forward in development of TC products based on ensemble forecasts (section 4).

2. **The current state of probabilistic prediction, probabilistic hurricane products, and their use.**

a. The evolving science of ensemble numerical weather prediction.

The workshop began with a series of review talks so that all participants had a common understanding of what can and cannot be expected from current-and planned ensemble systems. The reviews discussed TC predictability, ensemble system design, the treatment of model errors in ensembles, and post-processing techniques.

As specific as we might wish the forecasts to be, the rapid growth of errors in numerical forecasts will inevitably constrain the potential amount of certainty in the forecasts. The constraints vary with the scale of the phenomena. Heavy rain associated with individual thunderstorms may be predictable in a TC for only a fraction of an hour; the eye wall size and asymmetries for less than a day; the synoptic-scale environment for perhaps a week. No matter what ensemble system improvements are implemented, the rapid growth of errors will defeat attempts to predict much detail beyond these time ranges (Lorenz 1969, Tribbia and Baumhefner 2004). Still, during the time period while forecast errors are growing but have not yet saturated, ensembles are expected to provide the case-dependent estimates of that uncertainty. What are the challenges to improving ensemble predictions for TCs?

Concerning the initialization of ensembles in the tropics, the ensemble Kalman filter (EnKF; e.g., Houtekamer and Mitchell 1998, Hamill 2006) is a particularly promising approach that is being explored by many scientists. The EnKF may be able to provide sets of initial conditions that have reduced error, appropriate spread, and more realistic TCs in the initial conditions. Researchers are working with variational data assimilation experts at the National Centers for Environmental Prediction (NCEP) to hybridize the EnKF with its variational data assimilation system (Kleist et al. 2009). The EnKF is being demonstrated for TCs with global models (Hamill et al. 2010), and nested high-resolution regional EnKFs are being developed for TCs (Zhang et al. 2009, Wu et al. 2010, Torn 2010). Additionally, the U.S. Navy has recently updated their global data assimilation to a 4D-Var algorithm (Xu et al. 2005), and their operational ensemble initialization method was changed to a "banded" ensemble transform technique (McClay et al. 2010), both of which have improved TC track forecasts. Another approach to TC ensemble initialization is the use of diabatic singular vectors (Puri et al. 2001), used at the European Centre for Medium-Range Weather Forecasts (ECMWF).

An equally challenging problem in ensemble predictions is how to deal in scientifically sound ways with the significant errors introduced by model imperfections. Of course, some errors are introduced by the limited resolution at which ensembles can be conducted (Gentry and Lackmann 2010), and the use of limited-area domains can suppress the realistic growth of differences between members (Nutter et al. 2004) and affect the distribution of convection (Warner and Hsu 2000). However, large-domain, high-resolution ensembles are not currently computationally feasible on current generation production computers. Further, parameterizations of sensitive TC processes such as sea spray (Gall et al. 2008) are based on a limited understanding, in part due to lack of observations. We also lack a basic understanding of the cloud particle physics and aerosols in TCs. Intensity predictions are very sensitive to model coefficients such as the horizontal mixing length (Bryan et al. 2010), where the range of appropriate values is not well known. Ensemble predictions may also inherit many of the deficiencies of deterministic models, such as over-forecasting of TC genesis and difficulties in predicting rapid intensity changes (Kaplan et al. 2010).

Three general approaches can be used to deal with systematic errors in an ensemble prediction system. The first is to improve the forecast system, perhaps increasing the resolution, improving the fidelity of parameterizations, generating the ensembles with larger or global domains, and appropriately coupling predictive models for the state components such as the ocean and atmosphere. Such work is of course occurring; for example, NCEP has recently upgraded the resolution of their global ensemble forecast system to T190 (~90 km grid spacing at 30°N), and the deterministic model was upgraded in summer 2010 to T574 (~30 km grid spacing at 30°N), with upgrades to the radiative transfer code, shallow convection, planetary boundary layer (PBL), and deep convection routines. ECMWF recently upgraded their ensemble prediction system to T639 (Richardson 2010), which significantly reduced TC intensity biases.

The second general approach is to introduce stochastic effects to represent model uncertainty in a physically realistic fashion. One underlying problem is that many of the parameterizations are formulated deterministically; given the same large-scale input, the same response of sub-grid forcing upon the resolved scales is always predicted, even though a range of responses is plausible. Techniques that are being used in operations or are being tested include perturbing the parameterized tendencies with random numbers or structured noise (Buizza et al. 1999, Palmer et al. 2009), using an ensemble system with multiple parameterizations (Charron et al. 2010), and introducing stochastic aspects into parameterizations (Lin and Neelin 2002, Teixeira and Reynolds 2008, Plant and Craig 2008). At several centers, a "stochastic backscatter" scheme has been implemented to stimulate an upscale energy cascade that can be lost due to excessive numerical dissipation (Shutts 2005, Berner et al. 2009, Charron et al. 2010). Collectively, this is an area where much more research is needed, for many of the parameterizations in models are still deterministic, and many of the approaches taken currently are ad-hoc (i.e., they increase spread, but not necessarily for scientifically defensible reasons).

The third approach is to post-process. A simple approach may be to combine output from existing models. Goerss (2007) has shown the value of a multi-model consensus, if that is available. If various ensemble systems provide estimates of track with relatively independent systematic error characteristics, a consensus should provide some improvement. This technique has been used, at first subjectively, by forecasters at the National Hurricane Center (NHC) for more than a decade and currently provides among the best automated track guidance (Rappaport et al. 2009).

Another type of post-processing consists of applying statistical corrections based on discrepancies between past forecasts and observations. Krishnamurti et al. (2006) discussed the "superensemble" concept, combining regression-corrected ensemble guidance. When making statistical corrections, especially for a phenomena like a TC that may impact a given location only once every 5-10 years, it is helpful to be able to examine the characteristics of numerical guidance from similar past events. Reforecasts, a database of past forecasts using the same model and assimilation system, can provide just that (Hamill et al. 2006). ECMWF now operationally generates a 5-member, real-time reforecast once weekly, creating forecasts for the past 18 years (Hagedorn 2008, Hagedorn et al. 2010). For TCs, they use real-time reforecasts to calibrate their forecasts of TC genesis (Vitart et al. 2010). An even more extensive reforecast data set, with forecasts more often than once weekly, may be helpful for TC calibration.

b. Current probabilistic forecast tools and products.

The NHC currently uses a variety of forecast tools, some of which provide probabilistic information. Several of their forecast products contain probabilistic elements. We briefly review these tools and forecast products.

Among the forecaster tools, NHC can examine a "poor-person's" ensemble consisting of guidance from a range of deterministic models, including limited area models such as the GFDL model (Bender et al. 2007) and HWRF (Bao et al. 2010). NHC also has access to global deterministic forecasts from the GFS, the U.S. Navy's Operational Global Atmospheric Prediction System (NOGAPS; Peng et al. 2004); the UK Met Office global model (Bowler et al. 2008, 2009) and the ECMWF model (www.ecmwf.int/research/ifsdocs/). Additionally, they regularly examine ensemble guidance from the NCEP Global Ensemble Forecast System (GEFS) and the ECMWF ensemble system. Less attention is paid to ensemble output from other international centers. Given the errors associated with purely dynamical guidance, especially with intensity, NHC forecasters also routinely examine a variety of multi-model consensus forecasts (e.g., Goerss 2007), and they use statistical-dynamical intensity models such as SHIPS (Statistical Hurricane Intensity Prediction Scheme; DeMaria et al. 2005) and LGEM (Logistic Growth Equation Model; DeMaria 2009) for intensity forecast guidance. Because none of the intensity forecast models reliably predict rapid intensification, NHC also uses a Rapid Intensity Index (RII). The RII uses satellite observations and the NCEP global model forecast to provide a quantitative estimate of the probability of a rapid intensification in the next 24 h.

The NHC produces real-time products to convey the current and forecast location, intensity (wind speed) and size of TCs and their precursors, as well as associated effects (e.g., storm surge). Textual products with uncertainty information (see online appendix A for examples) include a tropical weather outlook, which provides probabilities of TC formation in the next 48 h, and a TC discussion providing forecaster reasoning and alternate scenarios based on model guidance diversity. Surface wind-speed probabilities based on a Monte-Carlo approach that considers on the order of 1,000 realistic track, intensity and size possibilities constitute another text product, provided in tabular format. Graphical forecast products include some with probabilistic elements: surface wind speeds, storm surge heights, a coastal watch/warning, and 3- and 5-day cone of uncertainty for TC center position (see online appendix A for examples). Local NWS weather forecast offices provide additional products (not shown).

3. **Recommendations for ensemble-related product development**.

Breakout groups produced recommendations for ensemble-related products that could be helpful to (a) forecasters, and (b) emergency managers and the media. Here, we have synthesized the recommendations for the two groups, though in fact the group recommendations differed somewhat in emphasis. The recommendations for forecasters focused more on products that permit a greater understanding of the information content of ensembles. Product recommendations for emergency managers and the media focused more on graphics that were visually intuitive, that helped them communicate uncertainty information to their audiences.

Emergency managers and media representatives preferred new uncertainty products to be simple and easily explainable to their customers who are most familiar with deterministic products. One modest change might be to enhance the deterministic products with some confidence index (low/medium/high) based upon ensemble uncertainty estimates. For newer graphics, training may be necessary before users embrace them. Explanatory web pages could be created and associated with the new product web pages. Additionally, through conferences and training facilities such as COMET (the Cooperative Program for Operational Meteorology, Education, and Training), advanced users could be trained in how to interpret the new probabilistic guidance.

Experimental ensemble-based products disseminated beyond the ranks of government forecasters should include appropriate disclaimers. They may note, for instance, that these products represent experimental guidance that may not produce reliable probabilities, and that they should not be considered "official" forecasts.

Below, we recommend products specific to intensity, genesis, track, and so on, focused on the needs of operational forecasters.

a. Intensity products.

The forecasters' greatest need is for improved intensity-related products, including the probability distribution of intensity change. This presents a considerable challenge given the current difficulties that ensemble systems (and deterministic models) have with predicting intensity change.

A relatively straightforward approach that should be investigated to improve guidance for forecasters would be to incorporate ensemble input into existing statistical models of intensity changes such as the LGEM. The open-water component of the LGEM consist of a differential equation that predicts intensity changes, of the form

$$\frac{dV}{dt} = \kappa V - \beta V \left(\frac{V}{V_{mpi}} \right)^n , \tag{1}$$

where V is the predicted maximum wind speed, V_{mpi} is the maximum-potential intensity wind speed, estimated by this model using sea-surface temperature (SST) information (DeMaria and Kaplan 1994, Whitney and Hobgood 1997) appropriate to the forecast track. $\kappa, \beta,$ and n are parameters that were estimated through a minimization process using a long climatology of observed hurricane track data and associated environmental information such as vertical shear and convective instability. A relatively simple method for providing an ensemble of intensity change forecast estimates would involve producing one intensity forecast for each forecast track of an ensemble. The LGEM output intensity change estimates would thus differ as the different tracks encountered different SSTs and atmospheric environments. An obvious difficulty with this approach may be that the ensemble of track forecasts will not realistically represent the variety of possible tracks; the mean position may be biased, and there may be insufficient diversity among track forecasts. Another limitation is that, although LGEM is skillful in terms of average forecast errors, it does not perform well with regard to rapid intensification. However, this method is computationally inexpensive, is easy to implement and would provide some initial experience with intensity forecast model ensembles.

Were a reforecast data set available (e.g., Hamill et al. 2006), forecast track statistics could be generated for a long period of time from a stable model. This approach may permit systematic track errors to be estimated and corrected from real-time forecasts. It may also be possible to train a model like LGEM not using analysis data (a "perfect-prog" approach), but rather using forecast data (a "model output statistics" approach), and in this way account for potential biases in forecasts of the environmental information.

Other products could also convey predictive information related to intensity to forecasters. Figure 2 provides a synthetic example of how a spaghetti plot of tracks could be augmented with intensity-related information; included on this plot is analyzed tropical cyclone heat potential (TCHP), defined as

$$TCHP = C_p \int_{z(0)}^{z(D_{26})} \left(T(z) - 26\right) \rho \, dz \tag{2}$$

where C_p is the specific heat capacity of sea water, $T(z)$ is the temperature in Celsius at depth z, ρ is the density of seawater, and the integration is performed from the depth of the 26°C isotherm, D_{26}, to the ocean surface. Values over 90 kJ/cm^2 are typically considered favorable for enhanced TC intensification. The arrows associated with each track position represent the associated vector 850-200 hPa wind shear. Also displayed are the forecast central pressures. A visual display like this permits a forecaster to see the interactions of several variables that may be related to intensity. In this case, for example, the wind shear is somewhat weaker and the TCHP larger at 48 h to the southwest, suggesting that if the storm takes a more southwesterly course, it may be stronger than a storm moving farther north. In this case, the intensity difference is also reflected in the model-forecast central pressure estimates.

"Meteograms" of the ensemble distribution could also be produced for intensity-related storm parameters, such as shear, mid-level moisture, instability, maximum wind speed, as illustrated in Fig. 3. Another possibility would be the creation of ensemble-derived probability maps of important variables, which might depict, for example, the probabilities of exceedance of critical variables, such as RH < 50% at 500 hPa, or 850-200 hPa vertical shear > 15 kts (~7.7 m/s). Finally, were a reforecast dataset available, an "Extreme Forecast Index" (LaLaurette 2006) could be created for intensity forecasts, representing how the ensemble of forecast intensities compare to the climatological distribution of forecast intensities.

b. Tropical cyclogenesis products.

Products to help predict the relative likelihood of TC genesis were also regarded as very important. However, given the common over-forecasting of genesis in numerical models, the potential skill of such products was expected to be marginal, at least until reforecasts are available to estimate the climatological frequency of genesis from past forecasts. At the workshop, D. Richardson of ECMWF presented how his organization calibrates the ensemble guidance of tropical cyclogenesis using the forecast climatology derived from their 20-year, once-weekly reforecast data set (Hagedorn 2008). Figure 4 illustrates how ECMWF represented the relative likelihood of TC genesis in several basins in their real-time forecast compared to the frequency of genesis determined from past forecasts.

The working group suggested that even without reforecasts, it may still be helpful to be able to evaluate numerical guidance of TC genesis from ensembles. This might include tracker output of model-generated storms and genesis probabilities estimated from the ensemble in geographical areas, especially at the 48-hour and 120-hour lead times. Another recommendation was to examine whether providing ensemble input into a statistical model of genesis (Schumacher et al. 2009) might be useful.

c. Structure products.

Ensemble products that provide information about storm structure, such as the forecast storm size and average wind radii at various thresholds in different storm quadrants, may be useful. Suggested products include ensemble averages of the radius of the outermost closed isobar (OCI), which provides one possible measure of overall storm size. Another proposal was to provide the ensemble-mean predictions of 34, 50, and 64-kt (15.4, 25.7, and 32.9 ms^{-1}) wind radii in different quadrants, where the ensemble of storms is relocated to a common position. Probability distributions of the OCI and wind radii might also be useful.

d. Track products.

In addition to the possibilities indicated in 3.a above for augmenting track information with intensity related variables, other recommendations were made for track-related products. For example, it was proposed that track information could incorporate lagged ensemble data and improved anisotropic, non-stationary estimates of the cone of uncertainty (Fig. 5). Such a plot could be further enhanced if the older forecasts had been subjected to quality control to eliminate or de-weight prior forecasts that did not match recent observed positions. Another suggestion was to perform cluster analysis to identify ensemble members for which storms have similar tracks, and create composite forecast fields for these clusters. For example, if the tracks exhibit some multi-modality, the synoptic pattern associated with each mode could be examined.

e. Associated phenomena: *storm surge, winds, rainfall, and tornadoes*.

As ensembles are improved and perhaps post-processed using reforecasts, they may provide more reliable track, intensity, and storm size estimates. These in turn may permit probabilistic guidance to be generated for many important storm-related effects. For example, storm surge probabilities might be generated by driving surge models like SLOSH (Sea, Lake, and Overland Surges from Hurricanes; Houston et al. 1999) with ensemble guidance. Similarly, post-processed ensemble guidance may provide improved estimates of precipitation from land-falling TCs (Hamill and Whitaker 2006) or from predecessor rain events (PREs; Galarneau et al. 2010). Statistical models may also make it possible to estimate tornado likelihood based on the environmental characteristics. Additional probabilistic forecasts could be generated for winds above critical thresholds such as tropical-storm or hurricane-strength and could provide information on the timing (onset, duration).

f. Guidance for locations of supplemental observations

Ensemble-based techniques may be useful for determining the most useful locations for supplemental observations. The observations may be dropsondes from reconnaissance aircraft or, in the future, the processing of higher-density cloud-track winds or satellite radiances. Typically, an ensemble-based targeting algorithm considers how much the forecast uncertainty (usually measured in this case as some function of the ensemble spread, i.e., the standard deviation about the mean) would be reduced as a result of the reduction in analysis-error variance in an ensemble due to the assimilation of extra data. These techniques are promising but are limited in their utility by the lack of calibration of the ensemble and the assumption of linear error growth (Majumdar et al. 2006; Reynolds et al. 2010).

4. Conclusions.

Studies indicate that users are able to make better decisions when provided with relevant uncertainty information. Ensemble prediction techniques for generating such information for TCs are rapidly increasing but are still subject to biases. As ensembles improve, the weather forecast community is planning for how to incorporate more ensemble-based uncertainty information into the forecast process and how TC uncertainty can be conveyed to forecasters, emergency managers, the media, and the public. Our 2010 workshop produced some preliminary ideas for how ensemble information can be interpreted and used more extensively. Special attention was given to new ensemble products for intensity forecasting, which have not improved as much as track forecasts over the past few decades. In general, forecasters were interested in products that were more diagnostic in nature, which would provide additional information about the range of possible outcomes. Emergency managers and the media were more interested in user-friendly graphics that could be understood readily by their customers.

This article is meant as a starting point for discussion, a way of engaging the community in thinking more broadly about how ensemble predictions can be leveraged in the forecast process. We welcome your contributions to this discussion.

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LIST OF FIGURE CAPTIONS

Figure 1: Conceptual illustration of how situationally dependent uncertainty such as provided by ensembles in track forecasts can improve decision making. In panel (a), the "cone of uncertainty" for a hurricane, estimated using the errors of prior forecasts, provides ambiguous information as to whether to evacuate a city. In panel (b), in this case a hypothetical calibrated ensemble is suggesting a narrower cone of uncertainty, indicating a decreased threat and implied commensurate actions for the city. Conversely, in panel (c), the uncertainty is much larger and encompasses most of the city, suggesting a potential different course of actions for the city.

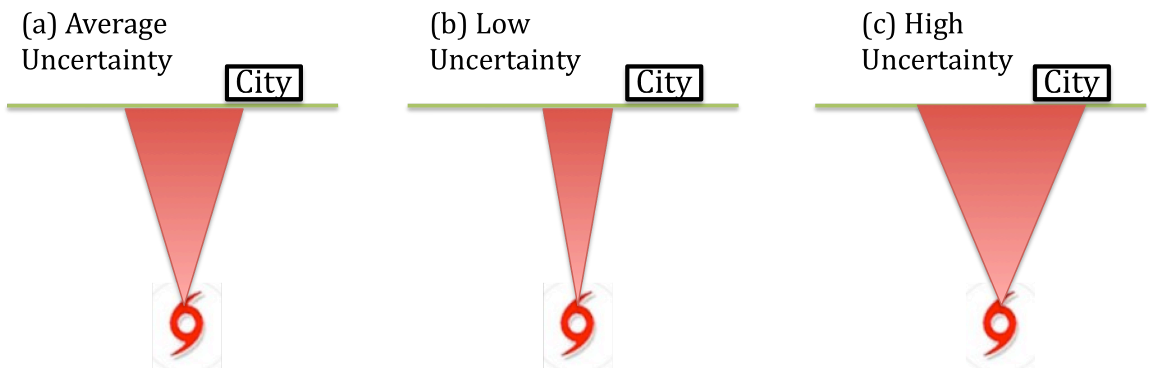
Figure 2: Illustration of a potential display of intensity-related information. A (synthetic) 10-member ensemble forecast of tracks are shown, with 0, 24, and 48-hour positions denoted by the dots. The underlying contours denote the analyzed tropical cyclone heat potential, as defined in the text; the wind barbs denote the vertical (200-850 hPa) vertical wind shear, measured in knots (1 knot = .5144 ms-1), The two numbers plotted over top the cyclone position denote the model-forecast mean sea-level central pressure, measured in hPa minus 900.

Figure 3: Synthetic example of a potential "meteogram"-style plot of intensity-related information from an ensemble system. Each panel provides the ensemble-mean forecast (solid line and dots), while the blue bars denote the lowest and

highest values from the ensemble. White lines denote the 20th and 80th percentiles of the distribution.

Figure 4: An example of ECMWF's extended-range forecast of tropical cyclogenesis, here for the week of 6-12 September 2010. Activity is monitored separately in the various basins, separated by the blue lines. The green bars show the mean number of TCs predicted to develop during the week 6-12 September (i.e., in each basin count all new TC geneses in each ensemble members in that 7-day period and calculate the mean of that number over the ensemble; the actual number is shown below the green bar). The orange bar (and number) is determined from the reforecast climate at this time of the year.

Figure 5: Lagged ensemble track forecasts for Hurricane Earl, 2010 from the GFS/EnKF (see Hamill et al. 2010). Light grey lines denote track forecasts initialized at 0000 UTC 31 August 2010. Darker grey lines denote track forecasts initialized at 1200 UTC 31 August 2010. Black lines denote track forecasts initialized at 0000 UTC 1 September 2010. Red dots denote positions of ensemble members, with the large red dot the position of the ensemble-mean member. The ellipse is from a fitted bivariate normal distribution, with the contour enclosing 90% of the fitted probability (ibid). Numbers indicate the forecast lead in days corresponding to the 1 September forecast.



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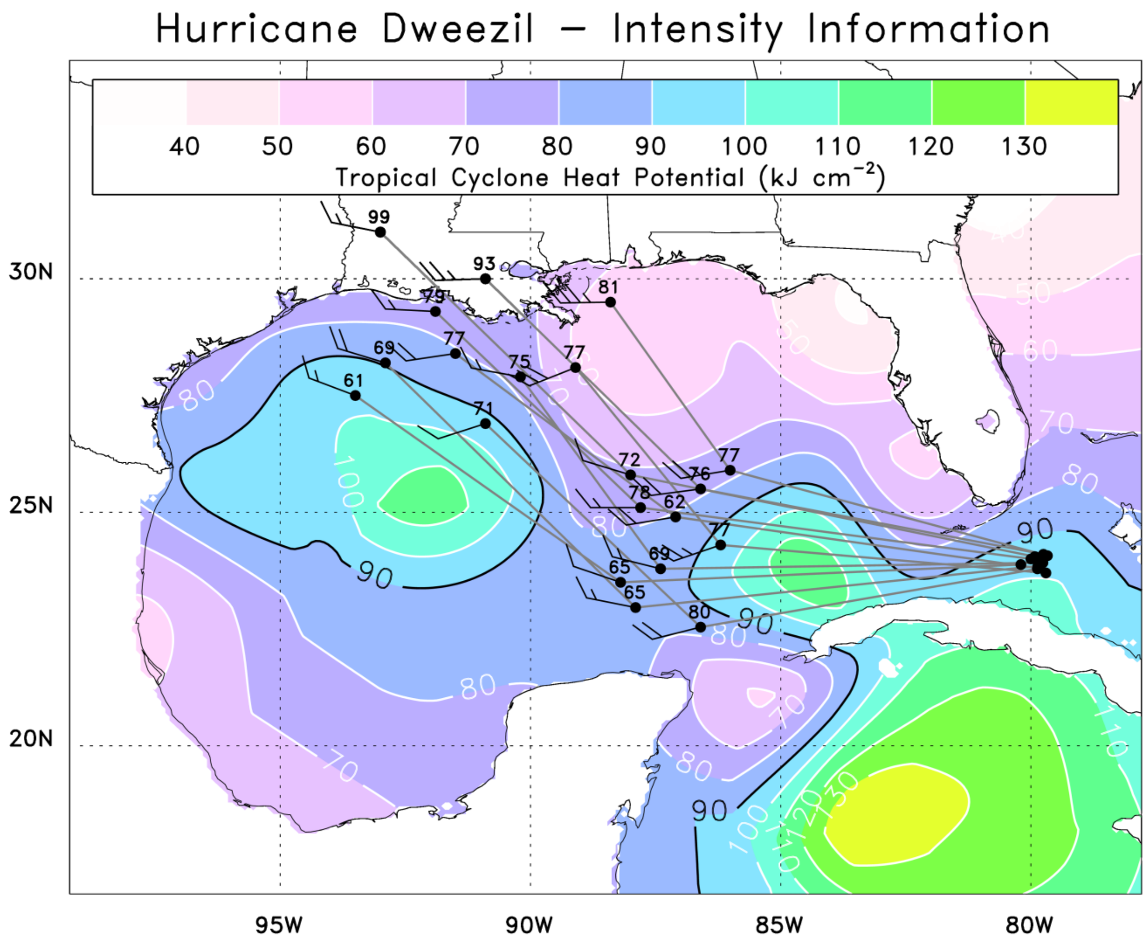

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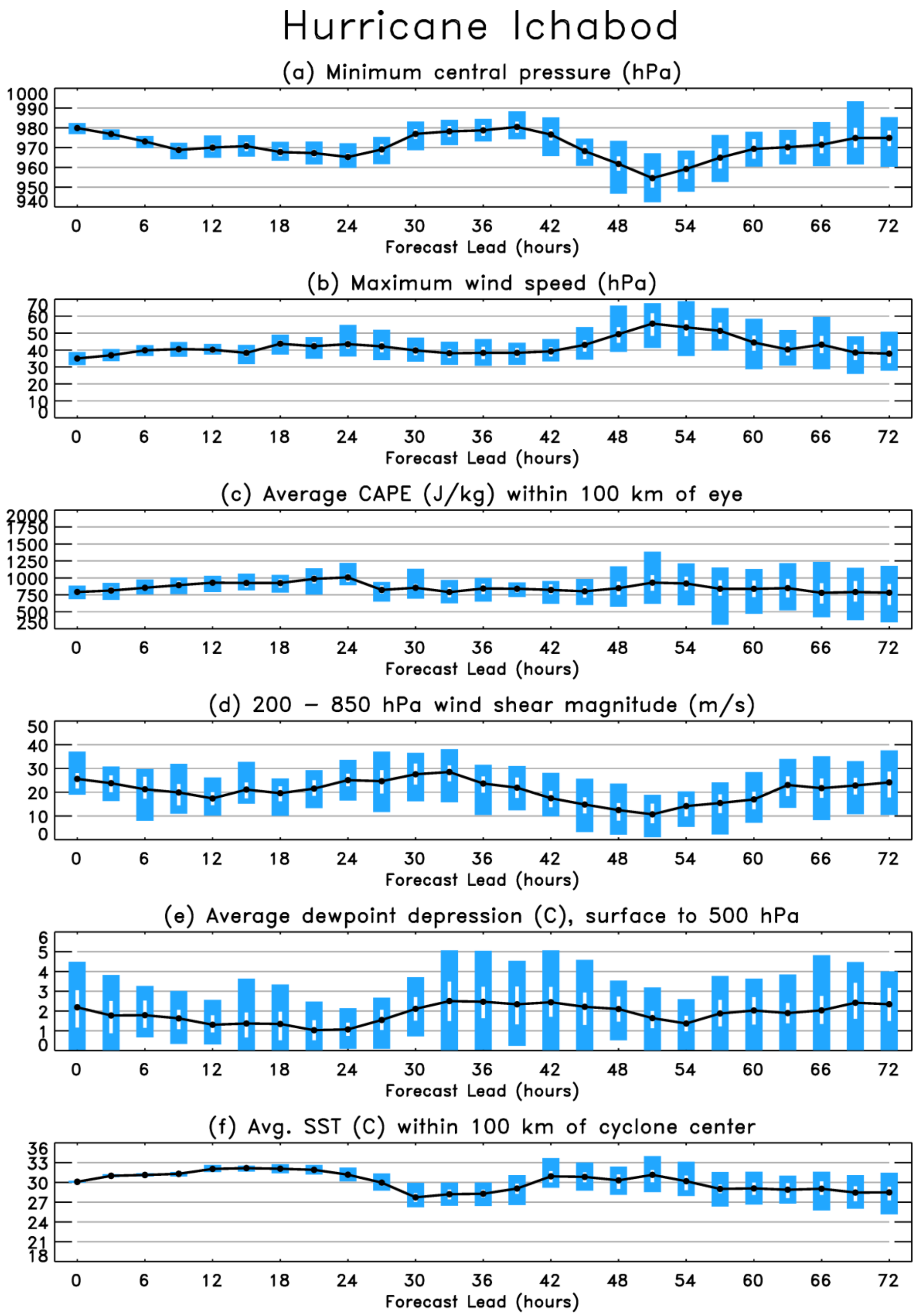

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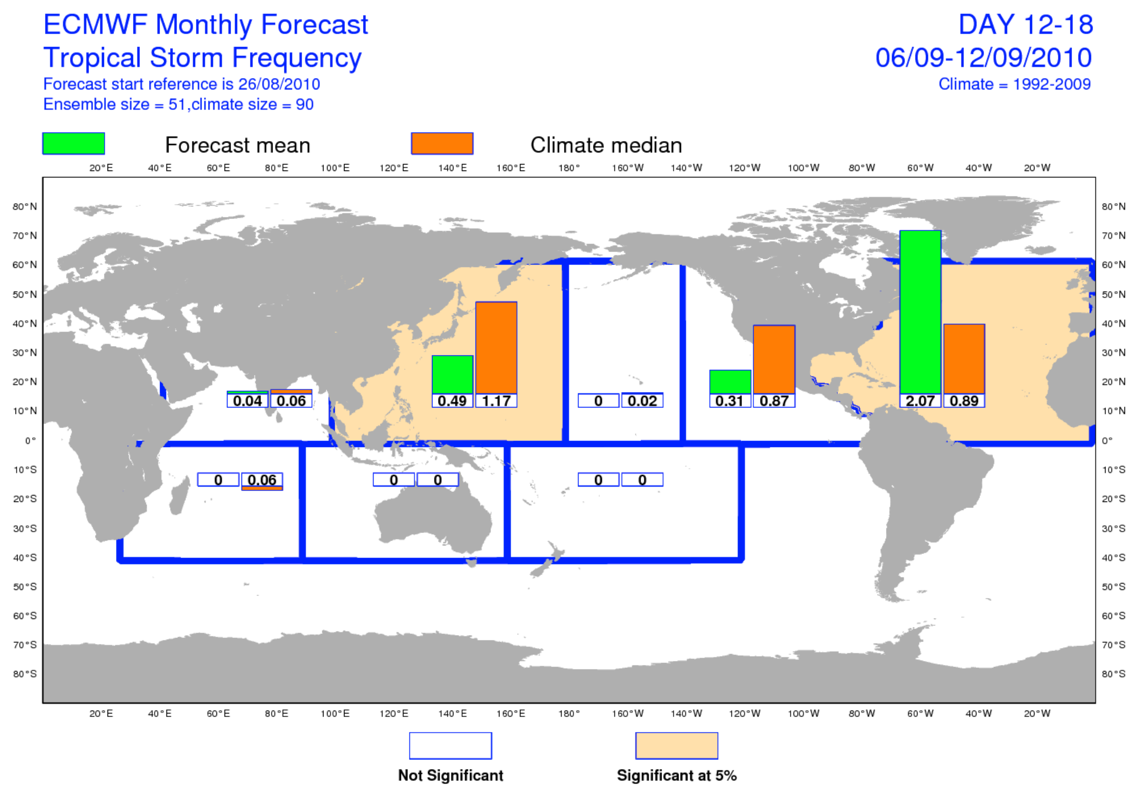

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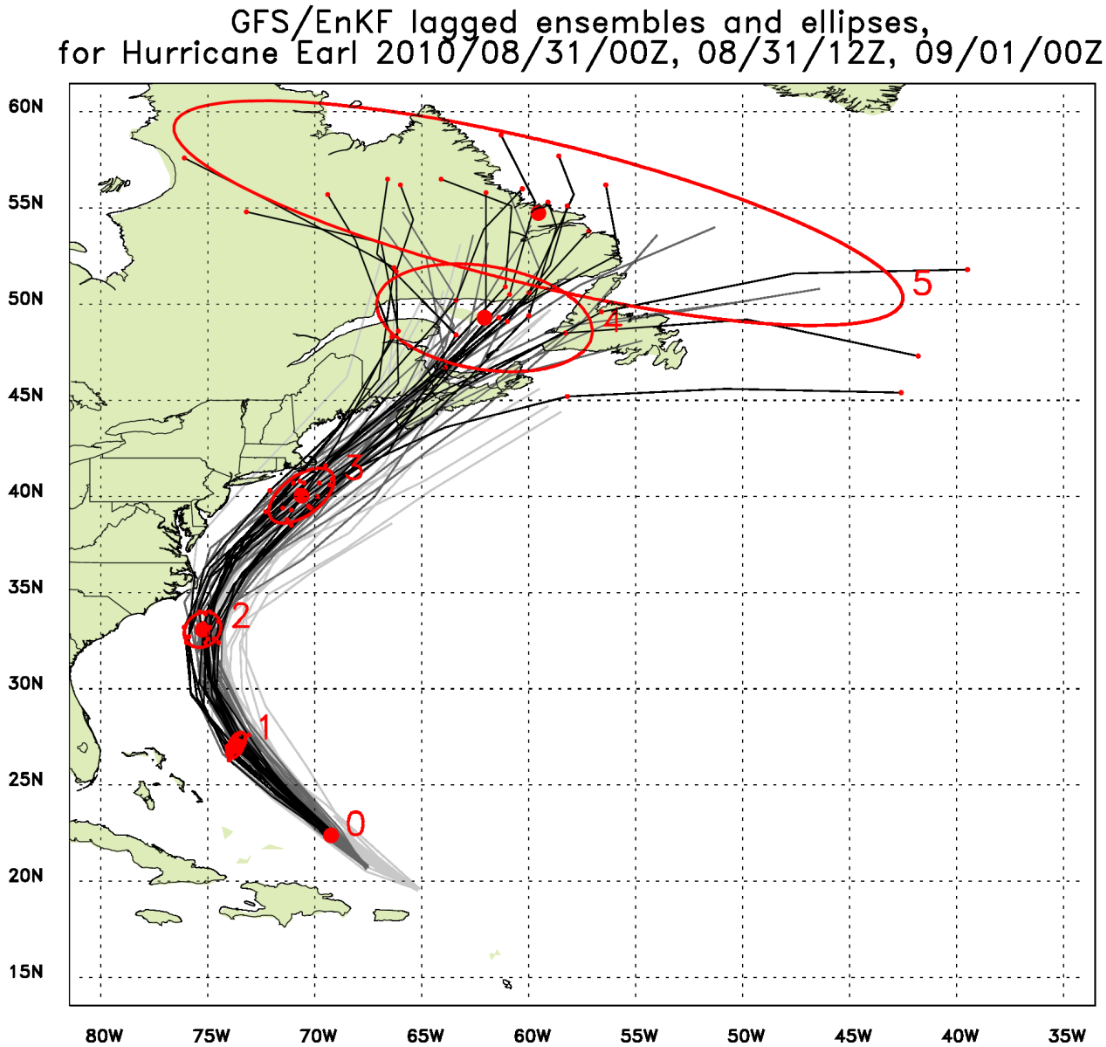

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